What does Willingness-to-Pay reveal about hospital market power in merger cases? †

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Abstract

In hospital merger cases, the courts have often based geographic market areas on patient flow criteria. Given patient heterogeneity and the importance of distance to hospital and health plan restrictions on hospital choice, Capps et al. (2003a) show that potential market power effects can be understated. While willingness-to-pay(WTP) measures derived from individual choice models provide an alternative assessment, antitrust law is, however, framed in terms of the likely price effects of mergers. This paper examines the connection between health plan prices and WTP that results from bargaining between managed care plans and hospitals. Empirically, we use merger cases in Florida and New York State to evaluate the accuracy of pre-merger predictions from patient-level choice models to assess mergers' effects on patients' aggregate WTP. Employing data available before a merger has occurred, we find that this method can provide reliable predictions of patients' post-merger willingness-to-pay, and thereby help inform the pre-merger investigation concerning likely price effects.

Key words: Hospital Mergers, Geographic Market Delineation, Patient Choice, Willingness-To-Pay, Conditional Logit

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Abstract

In hospital merger cases, the courts have often based geographic market areas on patient flow criteria. Given patient heterogeneity and the importance of distance to hospital and health plan restrictions on hospital choice, Capps et al. (2003a) show that potential market power effects can be understated. While willingness-to-pay(WTP) measures derived from individual choice models provide an alternative assessment, antitrust law is, however, framed in terms of the likely price effects of mergers. This paper examines the connection between health plan prices and WTP that results from bargaining between managed care plans and hospitals. Empirically, we use merger cases in Florida and New York State to evaluate the accuracy of pre-merger predictions from patient-level choice models to assess mergers' effects on patients' aggregate WTP. Employing data available before a merger has occurred, we find that this method can provide reliable predictions of patients' post-merger willingness-to-pay, and thereby help inform the pre-merger investigation concerning likely price effects.

1. Introduction

The hospital market experienced a surge in mergers and consolidations during the 1990s. Over 45% of U.S. hospitals were involved in mergers between 1990 and 1998 (Jaspen, 1998). During this period, courts often accepted the Elzinga/Hogarty (E/H) patient flow criteria to define the relevant hospital geographic market area.[1] In doing so, the courts agreed with the defendant's claims of a relatively large market area, and this ruling may have played a significant role in the loss of cases by Federal Trade Commission (FTC) and the Department of Justice (DOJ).[2]

This paper evaluates a recently proposed market area approach: the willingness-to-pay (WTP) methodology proposed in Capps et al. (2003a), Town and Vistnes (2001), and Capps et al. (2001).[3] Compared to previous methods, the willingness-to-pay methodology considers the merger's impact from micro-data on patient choices of hospital care, thus affording a richer recognition of the relevant impacts across heterogeneous patients and local areas much smaller than typical antitrust markets. Based on patients' preferences revealed by their actual choice behavior, we can evaluate welfare effects by how much more patients are willing to pay to include the merged hospitals in their choice set, and by inference, the effect of the merger on hospital prices.

The application of this methodology is a rather recent development in health economics. It has not been established how well an empirical model based on this approach performs in predicting post-merger impact or whether it might be a useful tool in merger analysis. Because merger challenges must be decided beforehand, it is worthwhile to consider the predictive properties of this approach under the constraints present in investigations limited by pre-merger data. We use patient discharge and other publicly-provided data to investigate, with hindsight, the reliability of this methodology in case studies from Florida and New York.

This paper addresses a number of policy and econometric issues. Section 2 examines the relevance for antitrust of willingness-to-pay measures and shows how changes in this measure relate to changes in insurance prices that result from Nash bargaining between health plans and hospitals. In Section 3, we estimate models using this methodology in the context of hospital merger case, one

[1]Details on E/H criteria are in Elzinga and Hogarty (1972) and Elzinga and Hogarty (1974). There is also a debate, ignored here, on whether it is correct to confine the hospital product market to only acute inpatient care (Sacher and Silvia, 1998).

[2]Since 1984, the FTC and DOJ have lost all eleven suits that were filed to block proposed hospital mergers. Specific cases are outlined in summary testimony by Capps, Dranove, Greenstein and Satterthwaite (2003b)

[3]Gaynor and Vogt (2003) and Kessler and McClellan (1999) employ similar structural models, although there are some differences in their models.

involving Columbia/HCA and HealthTrust in Florida in 1995 and the Long Island Jewish Medical Center case in 1997.[4] The key econometric results concern out-of-sample predictions. We imagine a pre-merger investigation that incorporates inferences about the merger's effects from data that are available *ex ante*. We examine the empirical properties of models using the WTP method for these mergers. With the hindsight of using previous merger episodes, we are able to calculate WTP for the merged hospitals using pre-merger data, and then re-estimate the model with data after the merger to estimate the post-merger WTP. We find that the model yields predictions that are fairly close to post-merger outcomes. It is thus worth considering whether the method achieves error rates that are acceptable to justify incorporating it in merger investigations under the *ex ante* data constraints present during the pre-merger period.

[4] 983 F.Supp. 121. United States v. Long Island Jewish Medical Center, E.D. NY. Gaynor and Vogt (2003) used San Luis Obispo County for analysis. Capps et al. (2001) and Capps et al. (2003a) used San Diego area as an example. These California areas have some specific features that may not be found in other states, including age, race and income composition as well as patient preferences.

2. Bargaining between MCO and Hospitals

The analysis of pricing in hospital markets must recognize the unique role of intermediation by payers on behalf of patients. Capps et al. (2003a) consider the hospital market as an 'option demand' market in which managed care organizations (MCO) negotiate with hospitals for contracts to provide care on behalf of customer/members.[5] Contracts determine what local hospitals are included in the network and the payments obligations of the plan. Consumers (or employers as their representative) then choose which network to join.

While the consumers' hospital choices may be restricted by the network, prices play little or no part in the choices made when episodes requiring hospital care arise. Members of the MCO plans, after paying the premium, face no variation in out-of-pocket prices as long as they go to a network hospital.[6] Patients choose hospitals based upon non-price characteristics of the hospital including distance to the patient's home, services offered, and ownership (Town and Vistnes (2001)). With empirical parameters estimated from a multinomial demand model, one can calculate patients' willingness-to-pay (WTP) for access to hospitals in the network.

The separation of consumption choices from the payments or fees for service in this market does not remove potential concerns about market power effects resulting from mergers. In antitrust law, hospital merger analysis remains focused on the effects on prices. But the usefulness of WTP measures for antitrust analysis requires some understanding of its link to prices, that has not previously been shown. We present a simple heuristic model to illustrate how hospital 'prices' relate patients' WTP and to show how hospital mergers may affect prices in option demand markets.[7]

2.1. **MCO-Hospital negotiations with capitation payments.** Assume that a local market has three hospitals present and consider the bargaining with a given MCO. The behavior of the MCO, constrained by other local health plan competitors, is assumed to maximize the utility of its enrollees and ignore any costs of MCO operations. The MCO negotiates individually with the three hospitals over payments and it may choose whether to include them in the network. The indirect

[5]The model in this section is adapted from Capps et al. (2003a), Capps et al. (2001) and McFadden (1998).

[6]Unlike Medicare and fee-for-service plans, managed care organizations rely more on per-member per-month payments with hospitals.

[7]For example, in the US vs. Evanston Northwestern Healthcare, the FTC official argued that managed health care plans no longer could negotiate lower prices after the merger by selectively contracting with either Evanston Northwestern or Highland Park Hospital. The merged system allegedly exploited its bargaining position to negotiate higher prices worth millions of dollars (Guerin-Calvert et al., 2005).

utility individual i gets from going to hospital j is:

$$U_{ij} = y_i - r + a_{ij} + \varepsilon_{ij} \tag{1}$$

where y_i is individual i's income. The payment r is the capitation payment reimbursed to hospitals per member, or, equivalently the premium paid by enrollees. The payment r is assumed to be actuarially fair and to be adequate to cover the cost of the hospital contracts in the network that the MCO arranged. For a three hospital network, $r = r_1 + r_2 + r_3$ covers the payments made to hospital 1, 2 and 3. a_{ij} is a vector of hospital j's characteristics, including its ownership, teaching status, nursing and capital (or equipment) intensity, services offered by hospital j, the travel time from patient i's home to hospital j, the patient's socioeconomic characteristics and the disease severity. When an existing MCO plan includes hospital j as well as k in the network, a patient will choose hospital j over k if:

$$U_{ij} - U_{ik} > 0 \Rightarrow a_{ij} - a_{ik} > \varepsilon_{ij} - \varepsilon_{ik} \tag{2}$$

Under the assumption that ε_{ij} and ε_{ik} are independently-distributed, extreme value random variables, the probability that patient i chooses hospital j, given the network G is:

$$s_{ij}(G, a_{ij}) = \frac{\exp(a_{ij})}{\sum_{k \in G} \exp(a_{ik})} \tag{3}$$

We analyze the MCO's problem by considering first what determines the selection of hospitals for the network when the payments r are exogenously given, and second, when r is explicitly negotiated. The expected maximum utility patient i can get from network G, given r, can be shown to satisfy[8]:

$$E \max_{j \in G}[y_i - r + a_{ij} + \varepsilon_{ij}] = \ln(\sum_{j \in G} \exp(y_i - r + a_{ij})) \tag{4}$$

The MCO's objective is to maximize its enrollees' total expected utility by choosing the configuration of the network, given r:

$$\max_G (\sum_{i=1}^{N} \ln(\sum_{j \in G} \exp(y_i - r + a_{ij}))) \tag{5}$$

[8]This result is a property of the standard extreme value distribution, ignoring the Euler's constant(-.57722) which does not affect the maximization problem. See e.g.Haab and McConnell (2003) and McFadden (1997).

For example, with three available hospitals and two hospitals already in the network, the MCO can negotiate to include the third hospital in its network if additional costs $r_3 * N$ are less than its additional benefit to the enrollees:

$$\sum_{i=1}^{N}(\ln(\sum_{r,G}\exp(y_i - r + a_{ij}))) > \sum_{i=1}^{N}(\ln(\sum_{r',G'}\exp(y_i - r' + a_{ij}))) \tag{6}$$

Where $r = r_1 + r_2 + r_3, G = (1, 2, 3), r' = r_1 + r_2, G' = (1, 2)$

This inequality can be simplified to:

$$N * r_3 < \sum_{i=1}^{N}[\ln(\exp(a_{i1}) + \exp(a_{i2}) + \exp(a_{i3})) - \ln(\exp(a_{i1}) + \exp(a_{i2}))]$$

The term on the right side of the inequality condition is the willingness-to-pay for hospital j, measuring the contribution of hospital j in network G to the aggregate patients' utility. Specifically, it measures the change in the maximum utility[9], summed over all patients, when hospital j is added to the network, given that the remaining hospitals in G are already present. We denote $WTP_j^i(G, a_{ij})$ for the WTP of hospital j to patient i and $WTP_j(G)$ is the WTP of hospital j for all N enrollees in MCO network G. Combining equation 6 with 3 gives the individual, $i = 1, \ldots, N$, and the aggregate WTP values:

$$\begin{aligned} WTP_j^i(G, a_{ij}) &= \ln\left[\frac{1}{1 - s_{ij}(G, a_{ij})}\right] \\ WTP_j(G) &= \sum_{i}^{N}\ln\left[\frac{1}{1 - s_{ij}(G, a_{ij})}\right] \end{aligned} \tag{7}$$

Similarly, $WTP_{jk}(G)$, the joint WTP of hospital j and k in MCO network G, i.e. the additional utility hospitals j and k together bring to the network:

$$WTP_{jk}(G) = \sum_{i}^{N}\ln\left[\frac{1}{1 - s_{ij}(G, a_{ij}) - s_{ik}(G, a_{ik})}\right] \tag{8}$$

Constraints that would be satisfied when the MCO includes all three hospitals[10] can be written as:

$$Nr_1 < WTP_1(G), Nr_2 < WTP_2(G), Nr_3 < WTP_3(G) \tag{9}$$

[9] Alternatively, it is the change in the maximum expected utility, considered prospectively, based on the probability distribution of illness or injury events and before the patient's medical conditions are known.

[10] Additional four constraints are $N(r_1 + r_2) < WTP_{12}(G), N(r_1 + r_3) < WTP_{13}(G), N(r_2 + r_3) < WTP_{23}(G), N(r_1 + r_2 + r_3) < WTP_{123}(G)$ It can be shown that when the three conditions in 9 hold, these last four will also hold.

The previous discussion assumes that r, the capitation rates paid to hospitals, are set exogenously. The second question to consider now is how those rates are determined under the MCO contract. We imagine a bilateral negotiation between MCO and each of the three hospitals and evaluate the Nash bargaining solutions. The Nash bargaining model is appealing for many reasons. The cooperative solution concept does not exclude the effect of competition among hospitals. As number of available hospitals in the market grows, the WTP for any given hospital will likely be reduced, leading to lower payments from the MCO. The Nash bargaining model abstracts from transaction costs, assumes that negotiations involving any efficient contract will succeed, and produces a contract where the surplus from trading be split evenly between parties. While the even split feature of the model may understate the bargaining power of either MCOs or hospitals, it is a well recognized solution.[11]

We assume if the hospital j is excluded from the network, it can earn Π_{0j} from other sources. If it is included, however, hospital j can earn $r_j * N - c_j * Q_j + \Pi_{0j}.$, where Q_j is the number of patients served. As for the MCO, the most socially efficient network configuration is to include all hospitals available into the network.[12] Therefore, the alternative for MCO is G/j if disagreement occurs.[13] Nash bargaining between the MCO and hospital j solves the following:

$$\max_r (r_j * N - c_j * Q_j + \Pi_{0j} - \Pi_{0j})(\sum_{i=1}^{N} \ln[\sum_{k \in G} \exp(y_i - r + a_{ik})] - \sum_{i=1}^{N} \ln[\sum_{G/j} \exp(y_i - r' + a_{ik})])$$

$$\Rightarrow \max(r_j * N - c_j * Q_j)(WTP_j(G) - N * r_j)$$

Assuming an interior solution, the equilibrium price is:

$$r_j = \frac{1}{2 * N}(WTP_j(G) + c_j * Q_j) \tag{10}$$

This result says that bargaining produces capitation rate that depends directly on the WTP and the costs of hospital care. Moreover, it leads to an equal split of the surplus between profit and net WTP.

[11]A large variety of bargaining situations might be appropriate to consider. Binmore et al. (1986) establishes the linkage between the Nash bargaining solution and sequential strategic approaches. Studies in health economics including Ellison and Snyder (2001)and Gal-Or (1999) also use the Nash Bargaining Solution to model the negotiation between suppliers and buyers.

[12]From a social planner's point of view, the total utility for a network consisting of all hospitals $\sum_{i=1}^{N} \ln(\sum_{j \in G} \exp(y_i - r + a_{ij})) > \sum_{i=1}^{N} \ln(\sum_{j \in G/j} \exp(y_i - r + a_{ij}))$, the total utility after excluding hospital j.

[13]The Nash bargaining solution results using the assumption of Ellison and Snyder (2001) that each hospital conjectures that all other hospitals will bargain successfully with the MCO in equilibrium.

Consider next what happens when hospital 1 and 2 merge and negotiate jointly with the MCO. The Nash bargaining solution between the merged hospitals and MCO involves:

$$\max((r_1 + r_2) * N - c_1 * Q_1 - c_2 * Q_2)(WTP_{12}(G) - N * (r_1 + r_2)) \tag{11}$$

In this case, the post-merger hospital prices are:

$$r_1' + r_2' = \frac{1}{2N}(WTP_{12}(G) + c_1 * Q_1 + c_2 * Q_2). \tag{12}$$

The combined payments to the two merged hospitals are higher following merger because $WTP_{12}(G) > WTP_1(G) + WTP_1(G)$. The extent of the price effect will depend on the level of costs; constraints in (9) require costs in the range $0 \leq c_1 * Q_1 \leq WTP_1$ and $0 \leq c_2 * Q_2 \leq WTP_2$. Letting $\Delta WTP_{12}(G) = WTP_{12}(G) - WTP_1(G) - WTP_2(G)$, the percentage increase in prices is bounded by :

$$(1/2)\frac{\Delta WTP_{12}(G)}{WTP_1(G) + WTP_2(G)} \leq \frac{(r_1' + r_2') - (r_1 + r_2)}{r_1 + r_2} \leq \frac{\Delta WTP_{12}(G)}{WTP_1(G) + WTP_2(G)} \tag{13}$$

For antitrust purposes, equation 13 has important implications. It suggests that the WTP captures a key leverage factor in the negotiation between MCO and hospitals. With Nash Bargaining, the MCO and hospitals will split the WTP. After merger, however, WTP is increased because $WTP_{12}(G) > (WTP_1(G) + WTP_2(G))$

Thus, while the WTP itself depends on the availability of alternative hospitals and their competition for inclusion in the network, mergers that effect large changes in WTP may result in corresponding increase in the rates paid to hospitals for patient care that would raise valid antitrust concerns about harm to consumers of the affected health plans.

2.2. **MCO-Hospital negotiations over reimbursement rates for services.** We can extend the model to consider the case where, instead of capitation payments, MCOs and hospitals negotiate over per-unit prices that the hospital receive as reimbursement for services. This formulation comes closer to the kind of negotiation commonly attributed to MCOs. We assume again that if the hospital j is excluded from the network, it can earn Π_{0j} from other sources. If it is included, however, hospital j can earn $\Pi_{1j} = p_j * Q_j - c_j * Q_j + \Pi_{0j}$. Q_j is the number of patients served and is determined *ex post* by the logit demand model of hospital choice. In general, Q_j will depend on the number and characteristics of other hospitals in the network.

Nash bargaining between the MCO and the first hospital, hospital 1 solves the following:

$$\max_{p_1}(\Pi_{11} - \Pi_{01})(\sum_{i=1}^{N} \ln[\sum_{k\in G} \exp(y_i - N^{-1}(p_1 Q_1 + p_2 Q_2 + p_3 Q_3) + a_{ik})] \tag{14}$$
$$- \sum_{i=1}^{N} \ln[\sum_{G/1} \exp(y_i - N^{-1}(p_2 Q_2' + p_3 Q_3') + a_{ik})])$$
$$\Rightarrow \max(p_1 * Q_1 - C_1 * Q_1)(-p_1 Q_1 + p_2(Q_2' - Q_2) + p_3(Q_3' - Q_3) + WTP_1(G))$$

where Q_j are the number of patients who choose hospital j in the three hospital network, while Q_2' and Q_3' are the patient volumes of hospital 2 and 3, respectively, when the contract with hospital 1 fails. The maximization problems yields three equations in the prices, p_1, p_2, and p_3:

$$p_1 = \frac{1}{2 * Q_1}(WTP_1(G) + p_2(Q_2' - Q_2) + p_3(Q_3' - Q_3) + c_1 * Q_1) \tag{15}$$
$$p_2 = \frac{1}{2 * Q_2}(WTP_2(G) + p_1(Q_1' - Q_1) + p_3(Q_3' - Q_3) + c_2 * Q_2)$$
$$p_3 = \frac{1}{2 * Q_3}(WTP_3(G) + p_1(Q_1' - Q_1) + p_2(Q_2' - Q_2) + c_3 * Q_3)$$

These conditions, compared to those in the capitation rate bargaining problem, include some extra terms because, in the event the contract with any one hospital fails, the MCO requires reallocating patients to the other hospitals in the network and that would change the cost of the plan whenever $p_i \neq c_j$. We consider the symmetric case where all hospitals are identical. Assume $a_{i1} = a_{i2} = a_{i3} = a_i$ and $c_1 = c_2 = c_3 = c$. The solution to the system of equations is:

$$p_1 = p_2 = p_3 = 3 * \frac{WTP_j}{N} + c = 3\ln(\frac{3}{2}) + c. \tag{16}$$

where WTP_j is the marginal willingness to pay for any one hospital. The solution thus shows that each hospital extract their marginal WTP and earns profits $\Pi = N\ln(\frac{3}{2})$. While this example assumes three identical hospitals, when there are many hospitals, prices converge to competitive levels. When the number of hospital is J, it can be shown that in a symmetric case, $p = J\ln(\frac{J}{J-1}) + c$. As the number of hospitals increases, hospital prices approach equality with marginal cost c.

The configuration chosen for the network depends on the utility of the MCO, given the set of hospitals and prices. For instance, including $G = (1, 2, 3)$ yields utility to the MCO plan members equal to :

$$U = \sum_{i=1}^{N} \ln[\sum_{k \in G} \exp(y_i - N^{-1}(p_1 Q_1 + p_2 Q_2 + p_3 Q_3) + a_{ik})] \tag{17}$$
$$= \sum_{i=1}^{N} \ln[\exp(y_i - p + a_i) + \exp(y_i - p + a_i) + \exp(y_i - p + a_i)]$$

With prices determined by the Nash bargaining solution, this expression simplifies to:

$$U = \sum_{i=1}^{N} [\ln(3) + y_i - (3\ln(\frac{3}{2}) + c) + a_i] = \sum_{i=1}^{N} (y_i + \ln(\frac{8}{9}) + (a_i - c)) \tag{18}$$

As long as $\sum_{i=1}^{N}(a_i - c) > N\ln(\frac{9}{8})$ the utility from a network composed of $G = (1, 2, 3)$ will be greater than the utility with no hospitals in the network. At the margin, what is important in the symmetric case is the difference between $U(G = 1, 2, 3)$ and $U(G = 1, 2)$, i.e. the difference in the MCO utility between including all three hospitals in the network and including all but the last one. This difference in the three hospital case is equal to $\sum_{i=1}^{N} \ln(\frac{2^4}{((3)(1))^2}) = N * 1.778 > 0.$[14]

Now assume hospital 1 and hospital 2 merge. The post-merger Nash bargaining problem for hospitals 1 and 2 jointly is:

$$\max_{p_1, p_2}(p_1 * Q_1 - C_1 * Q_1 + p_2 * Q_2 - C_2 * Q_2)(-p_1 Q_1 - p_2 Q_2 + p_3(Q_1 + Q_2) + WTP_{12}(G)) \tag{19}$$

For hospital 3, the bargaining problem is:

$$\max_{p_3}(p_3 * Q_3 - C_3 * Q_3)(-p_3 Q_3 + p_1(Q_1' - Q_1) + p_2(Q_2' - Q_2) + WTP_3(G)) \tag{20}$$

These maximization problems yield two equations in the prices, p_1, p_2, and p_3.

$$p_1 Q_1 + p_2 Q_2 = \frac{1}{2}(WTP_{12}(G) + p_3(Q_1 + Q_2) + c_1 * Q_1 + c_2 * Q_2) \tag{21}$$
$$p_3 = \frac{1}{2 * Q_3}(WTP_3(G) + p_1(Q_1' - Q_1) + p_2(Q_2' - Q_2) + c_3 * Q_3)$$

Assume again the symmetric case, where $a_{i1} = a_{i2} = a_{i3} = a_i$ and $c_1 = c_2 = c_3 = c$. The solution to the system of equations is:

$$p_1 = p_2 = \frac{WTP_3(G)}{3Q} + \frac{WTP_{12}(G)}{3Q} + cp_3 = 2\frac{WTP_3(G)}{3Q} + \frac{1}{2}\frac{WTP_{12}(G)}{3Q} + c. \tag{22}$$

[14] In general, the difference between $U(G =, ..., J + 1)$ and $U(G = 1, ..., J)$, i.e. the marginal utility to the MCO from including the last hospital in the network is $U(G = J + 1) - U(G = J) = \sum_{i=1}^{N} \ln(J^{2J})/((J + 1)(J - 1))^J) > 0$.

The interpretation of this solution may be expressed in terms of the impact on the cost of the insurance plan. The insurance payment that is required from each MCO enrollee to meet all expenses with these reimbursement rates is equal to:

$$\begin{aligned}\overline{p} &= \frac{p_1 Q_1 + p_2 Q_2 + p_3 Q_3}{N} \\ &= \frac{4}{3}\frac{WTP_3(G)}{3Q} + \frac{5}{6}\frac{WTP_{12}(G)}{3Q} + c.\end{aligned} \tag{23}$$

Compared to the pre-merger cost of insurance $p = \frac{WTP_1(G)}{Q} + c$, the hospitals receive higher payments that depend on $\Delta WTP_{12}(G)$ of the combined hospitals:

$$\overline{p} - p = \frac{5}{18Q}(\Delta WTP_{12}(G)) = \frac{5}{6}\ln(\frac{4}{3}) \tag{24}$$

Thus, costs of insurance mirror the changes in the bargaining strength of the merged hospitals. To reiterate, we have shown for contracts based on capitation payments to the hospital and those where reimbursement rates are set for hospital care, there is a close correspondence between the merger's effect on WTP and the resulting prices. In acting as intermediary, the MCO seeks the best terms for members as a whole and does not discriminate in setting member fees. The value of the WTP measure is that it imputes effects that can vary considerably by the geographic location of the MCO members. These effects may be overlooked when confining attention to fixed sets of competitors in the market.

3. Empirical Analysis of Mergers in Palm Beach County, FL and Long Island, NY

We approach the empirical testing by selecting mergers that were likely to reflect significant change in a local hospital market, and for which enough time had elapsed to allow a retrospective analysis. In 1994, Columbia announced the acquisition of HealthTrust. By that time, Columbia operated 195 hospitals and HealthTrust operated 116 hospitals nationwide. The combined company had more than $15 billion in sales, with hospitals in 37 states. (Lutz and Pallarito (1995)).[15] In April 1995, when Columbia/HCA Healthcare and HealthTrust announced the completion of the merger for those units located in Florida, it had 17 hospitals in South Florida. Shortly after, in July 1995 Columbia/HCA acquired 369-bed JFK Medical Center in a nearby town of Atlantis.

We selected these Florida mergers for evaluation because of their size and other reasons.[16] The two acquisitions gave Columbia/HCA control of four hospitals in Palm Beach county.[17] Interestingly, one month after the JFK transaction, Columbia closed JFK Medical Center's long-time rival Palm Beach Regional Hospital in Lake Worth. Finally, from the standpoint of empirical evaluation, a convenient feature of the two Florida mergers is that they were completed within a very short time period in 1995, thus facilitating a comparison of pre- and post-merger results.

We also analyze the 1997 merger between Long Island Jewish Medical Center and North Shore Health System in New York. This case clearly illustrates the importance of heterogeneity in the patient choice sets within geographic market areas as they are typically defined in hospital merger cases. Before the merger, in 1995, Long Island Jewish Medical Center had 591 beds in service and total assets of $386 million. It was a prestigious teaching hospital serving residents in Queens County and Nassau County. Three miles away was North Shore University Hospital, a 729-bed prestigious teaching hospital, also serving residents in Queens and Nassau County. Its parent firm, North Shore Health System, operated 9 hospitals with 3,231 beds in 1995. Total assets of the nine hospitals were around $1 billion. (Pallarito (1997).)

[15] Their hospital systems overlapped broadly in Texas, Florida, Tennessee and Utah. The FTC raised serious concerns on the issue of market power after mergers. To win approval from the agency, the company was required to divest three hospitals in Utah, two hospitals in Florida, and one hospital in both Louisiana and Texas.

[16] Hospital officials said the JFK transaction was the single largest hospital sale to an investor-owned system since the 1984 sale of Wesley Medical Center in Wichita, Kansas, to Hospital Corporation of America for $265 million. (Lutz (1994)).

[17] Before the merger, Columbia Hospital in West Palm Beach is controlled by Columbia/HCA, Palms West in Loxahatchee and Palm Beach Regional near Lake Worth are controlled by HealthTrust, and JFK Medical Center, less than three miles away, is an independent hospital.

The DOJ, in its *Complaint* filed in District Court, focused mainly on the two hospitals' function as *anchor* hospitals.[18] Both are prestigious teaching hospitals offering a wide range of high quality services. Residents in Queens and Nassau County all wanted to have at least one of the hospitals in their insurance network. Although there were many other hospitals in this area, none of them had the capacity to substitute as an anchor hospital. Including one of the anchor hospitals in the network signified the quality of the insurance and was essential the insurance plan's marketability. Thus, the merger would prevent the insurance company's ability to substitute one anchor hospital for the other limit their able to negotiate separately with the two hospitals for lower prices. DOJ contended that the merger would force insurance rates to increase by 20%. (McQuiston (1997).)

In response, the hospital attorney argued that the merger was motivated by efficiency gains and it would be infeasible for the two merged hospitals to significantly increase their market power because they were in a wide geographic market consisting of 42 other hospitals in four counties, including Manhattan. (Bellandi (1997).)

In the next section, we describe the sampling methods used to select hospitals and patients and identify the variables specified in the analysis. The following sections report the empirical findings for the Palm Beach and the Long Island merger.

3.1. **Data Sample and Variables for the Palm Beach Merger.** Data for this study are taken from public use sources from Florida that contain financial measures for short-term acute care hospitals as well as patient discharge records covering all inpatient hospital stays. The sampling methods used to select hospitals and patients in Florida yield a market area that includes the 15 acute care hospitals in Palm Beach County, plus 5 other hospitals in neighboring counties that served less than 2 percent of the total patients. To get this result, it must be noted at the outset that the sampling design was subject to certain considerations. Consistent with patient flows analysis, the service area should be self-contained for each hospital under study. This means, first, that the analysis should not overlook any other "outside" hospitals where evidence reveals that patients in the local area are able to choose, and sometimes actually choose, for hospital care. These outside hospitals are a source of competition for the hospitals involved in the merger. Second, the data set

[18] 983 F.Supp. 121. United States v. Long Island Jewish Medical Center, E.D. NY June 11, 1997.

should include substantially all of the patients that received services from hospitals involved in the mergers, without restricting those patients by how far away they reside from the hospital.

Unlike the patient flows approach, however, we compute aggregate willingness of patients to pay for access to hospitals within diverse zip-code level choice sets. Varying the hospital choices by small areas allows for considerable heterogeneity within the total service area of any given hospital.

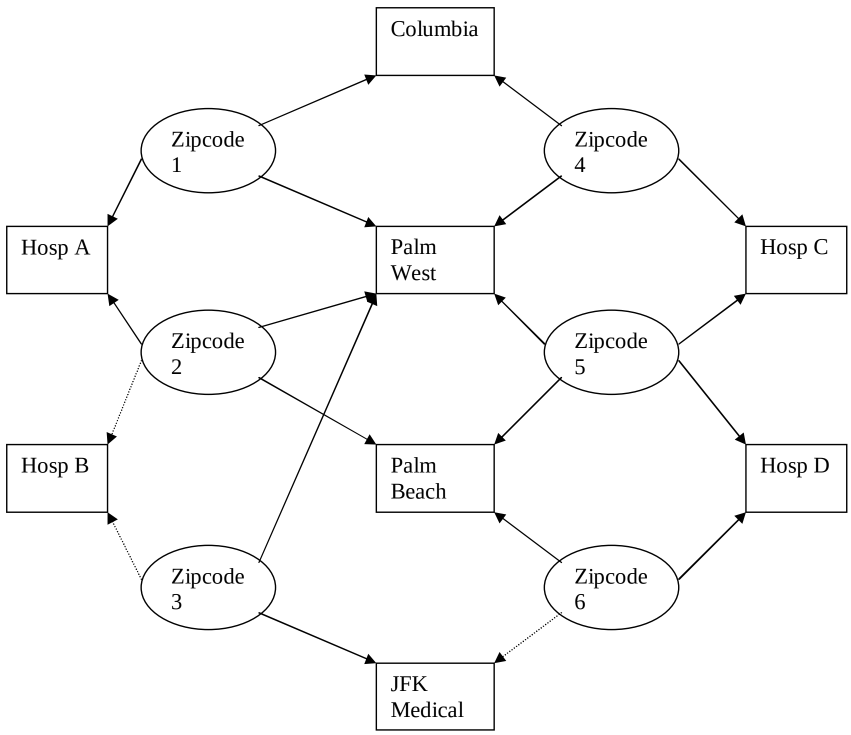

FIGURE 1. Hospital market area for the Palm Beach merger sample

We started with a sample containing, with only minor exceptions, a complete set of observations on all patients discharged from the four hospitals involved in the mergers. Figure 1 illustrates, in principle, how the market is defined in our study. The four boxes in the middle represent the four hospitals involved in the mergers. First we find all the zip codes for the patients who were discharged from these four hospitals. In this example, patients from zip code $1, 2, 3, 4, 5$ and 6 received care at the four hospitals. Then, looking at each zip code, we construct the full choice set of hospitals that draw patients from these locations. In the figure, patients from the 6 zip codes also visited hospital A, B, C and D. In the Florida data, there are 16 other hospitals whose service areas overlap our 4 focal hospitals, however, the percent of the hospitals' total discharges included in the sample, i.e. the hospital coverage rates, are low.

Some zip codes were excluded if very small numbers of patients are drawn to the four focal hospitals.[19] In the final sample, we account for 90,113 patients in total, over 92% of all patients treated in areas served by these hospitals. Thus, subject to these exclusions, the sample contains essentially all patient discharges in the areas where the four focal hospitals compete. Similar patient choice sets are constructed for the 1997 post-merger data.

After selecting hospitals and patients in our study, we estimate the following conditional logit model with choice sets that vary by patient zip code location:

$$P_{ij}(G, X_i, \lambda_i) = \frac{a_{ij}\exp(\alpha R_j + H_j'\Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} R_j)}{\sum_{k=1}^{J} a_{ik}\exp(\alpha R_k + H_k'\Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} R_k)} \tag{25}$$

Where $a_{ij} = 0$ if choice j is not available to individual i.

where the specification of the explanatory variables closely approximates those in Capps et al. (2003a):

$H_j = [R_j, S_j]$, R_j is a vector of hospital j's characteristics, including its control types (for profit, not for profit, or government), teaching status, nursing intensity, capital intensity etc. S_j are services offered by hospital j. R_j and S_j are from hospital financial data collected by state regulators.[20]

T_{ij} is the travel time from patient i's home to hospital j. These measures of distance to the hospital are from a public source, www.mapquest.com.

X_i include detailed clinical and demographic information from the public use inpatient discharge database in Florida: diagnoses (DRG code),[21] length of stay, payer category (Medicare, MCO etc.), patients' demographics (age, race, sex etc.), and patient zip code locations. Income data are taken from the Census.[22]

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[19] In a separate appendix, we discuss these sampling issues at length and explore the sensitivity of the model's predictions to changes in the sampling design.

[20] The data is collected by the Florida Agency for Health Care Administration (AHCA) using the hospital uniform reporting system. Currently 238 Florida hospitals are required to submit fiscal year end financial reports to AHCA.

[21] Patients' diagnoses and procedures are coded based on DRG and MDC. Except for the approximately 1.8% patients in MDC 25, 20, 2, 24 and 22 that were coded as "others", the diagnoses are aggregated up to MDCs.

[22] Income from the 1990 Census was obtained from 1990 Summary Tape File 3 (STF 3) at http://www.census.gov/main/www/cen1990.html. Income from the 2000 Census, Census 2000 Summary File 3 (SF 3) - Sample Data at http://www.census.gov/main/www/cen2000.html These sources provide per capita income by zip code and race in Palm Beach County. Income in 1994, the mid year between the census years, thus can be calculated as the average of the 1989 and 1999 income after adjusting price change using the BLS' release of CPI-U-RS April 27 2005, at http://www.bls.gov/cpi/cpiurstx.htm.

To calculate the total WTP for a hospital, estimates are required of patients' conditional probability for each type of disease, the mean length of stay, the mean Charlson severity index, and the mean number of diagnoses and procedures for a given condition. Using statewide patient discharge data from 1993 to 1995, we calculated these variables separately by demographic groups defined on patients' race, income, gender and age. A summary of variables is given in table 1 and sample statistics for patient characteristics are shown in table 2.

3.2. **Empirical Results from the Palm Beach, FL Mergers.** Table 3 reports the estimation results from the sample that includes all patients insured by commercial insurance, Medicare, Medicare-HMO, commercial HMO and commercial PPO.

The estimated coefficients for the most part, are highly significant, including those associated with dummy variables for for-profit status, nursing intensity, capital intensity, and hospital services offered. As previous research has shown, the travel time to the hospital and its interaction with other terms in the model are all very significant. In general the model is successful in capturing the key features of the choice set, and is broadly consistent with the results obtained in the earlier analysis of Capps et al. (2003).[23]

Within the assumptions of the conditional logit model, we can make out-of-sample predictions about changes in the willingness-to-pay following a merger. We focus on out-of-sample robustness, i.e. how well the model can predict, prospectively, how much the merger will change the aggregate value of WTP for the combined hospitals.

Prior to knowing what her disease/injury status will be,[24] individual i's WTP to include hospital j in network G is computed by evaluating the potential WTP over her entire set of possible medical conditions Z. Denote $p(Z_i|y_i)$ the probability of individual i having disease Z_i conditional on her socioeconomic attributes and location. The estimated WTP can be expressed as:

$$WTP_j^i(G, a_{ij}) = \sum_z \ln\left[\frac{1}{1 - s_{ij}(G, a_{ij})}\right] p(Z_i|y_i) \tag{26}$$

[23] A few of the point estimates in our model are different from Capps et al. (2003). The estimated coefficient on travel time to the hospital is smaller in magnitude than the earlier study (-0.068 compared to -0.2562). Moreover, the control variable for hospitals having organ transplant services increases the probability of being chosen by the patient in both papers, but the point estimate of the coefficient on this dummy variable is much larger in our paper (2.163 compared with 0.3693). The point estimates on these variables are not, however, the corresponding marginal effects because they depend on the extensive interaction terms in the model. Therefore, despite the differences, the marginal impacts may be similar.

[24] Capps et al. (2003a) refer to this prior as the *ex ante* WTP, while, after the health status is determined, the individual expresses an *ex post* WTP.

Summing over all patients who have hospital j as an alternative in their choice set gives the population's WTP for hospital j:

$$WTP_j(G) = \sum_{i=1}^{N} \sum_{z} \ln \left[\frac{1}{1 - s_{ij}(G, a_{ij})} \right] p(Z_i|y_i) \tag{27}$$

Similarly, the predicted post-merger WTP for merged hospital j and k is:

$$WTP_{jk}(G) = \sum_{i=1}^{N} \sum_{z} \ln \left[\frac{1}{1 - s_{ij}(G, a_{ij}) - s_{ik}(G, a_{ik})} \right] p(Z_i|y_i) \tag{28}$$

The willingness to pay for hospital j in equation 27 and the predicted WTP change implied by equation 28 are the main products of the model, in turn, affecting the post-merger price changes. If their measurement is imprecise, the predictions about future price changes will also be unreliable.

To evaluate the reliability of out-of-sample prediction, we predict WTP using pre-merger data, then repeat estimation on post-merger data to calculate the estimated post-merger WTP. Suppose hospital j and k merge and denote the pre-merger prediction of post-merger WTP, $\widehat{WTP}_{jk}(G)$. Next, post-merger data is used to estimate equation 25 and calculate the estimated post-merger WTP for j and k, $\widetilde{WTP}_{jk}(G)$. The difference is $\Delta WTP_{jk}(G) = \widehat{WTP}_{jk}(G) - \widetilde{WTP}_{jk}(G)$, i.e., our measure of the prediction error of the model from the two data sets pre-and post-merger. Traditional t-tests or other statistics assume either the difference would have the t-distribution or else one model is a nested version of the other. These conditions are clearly violated in our case. We resolve this problem by using bootstrap methods.[25]

The left side of table 4 reports the results obtained for $\widehat{WTP}$ from the 1994 data. The results to the right of the table summarize $\widetilde{WTP}$, based on estimated parameters from the 1997 post-merger data.[26] Bootstrap methods on 100 pseudo-samples were used to analyze the empirical distribution of the difference of the two estimated WTPs.

[25]We draw, with replacement, n pseudo samples, each with N observations from the original pre-merger data. Similarly, we create n pseudo samples from the post-merger data. The model is re-estimated for each pseudo-sample, and the repeated estimates are used to obtain $\widehat{WTP}$, as well as post-merger estimate $\widetilde{WTP}$, and take the difference.

[26]For comparisons across the two sample years, one further adjustment is necessary to account for the fact that, due to growth, the inpatient volume is different between 1994 and 1997. To accommodate this change, let $N97$ the number of patients in 1997, and $N94$ is the number in 1994, for the later year, $\widetilde{WTP}$ is multiplied by $N94/N97$ to give a scaled value. This adjustment is equivalent to assuming that there is a neutral, aggregate demand growth, which seems reasonable for the state of Florida during these years.

The mean difference between the *ex ante* predicted changes and the *ex post* estimated changes was found to be only 3.9%. Thus, it would appear that this methodology can provide excellent out-of-sample prediction, and may be reliable enough for its intended use. The Palm Beach mergers are associated with substantial changes in WTP, on the order of about 20%. Further, as our earlier bargaining analysis suggests, we can infer qualitatively similar profit and price changes within small confidence intervals.

Our results can be compared with the Elzinga/Hogarty (E/H) method. Based on the patient follow criteria, the 15 hospitals in Palm Beach County constitute a relevant geographic market, and all patients are assumed to have access to the full set of hospitals.[27] Consequently, the pre-merger Herfindahl Hirschman Index, HHI is 898, while the post-merger HHI is 984, an increase of only 86 points. Under prevailing merger guidelines, the market is considered to be unconcentrated and these mergers are unlikely to have adverse competitive effects. But the mean change in WTP is 24%, and would signal the need to examine the merger more closely.

The sample used to this point includes patients who are insured under a variety of insurance plans: commercial fee-for-service, Medicare, Medicare-HMO, commercial HMO and commercial PPO arrangements. Emergency admissions are also included. Clearly, sampling from such diverse groups of patients may introduce two problems. First, the Medicare program reimburses hospitals on the basis of a fixed price per admission for treatment and does not bargain with individual hospitals. Reimbursement rates would not change simply because local hospitals merge. Second, the inclusion of emergency admissions in the conditional logit model may generate biased estimates since in most emergency admissions, the choice of hospital is not made by patients but by other hospital assignment mechanisms used by emergency personnel, chiefly distance to the hospital.

To alleviate these problems, we have taken a two step approach. First, we estimated the conditional logit model using observations only on Medicare, commercial insurance, HMO, and PPO patients who were non-emergency admissions to obtain the parameters of the choice model. Second, we then use the estimates to calculate the WTP for observations on the remaining, commercial HMO and PPO patient observations. This procedure helps to eliminate the potential confounding effects, because the changes are limited to the sample that contain commercial HMO and PPO patients,

[27]The two criteria are termed Little In From Outside (LIFO) and Little Out From Inside (LOFI). In Palm Beach County, FL, LIFO =92% and LOFI = 89%

those most directly affected by mergers, and non-emergency patients, those most likely to influence their choice of hospital.

Table 5 reports the change in the estimated willingness to pay from pre-merger data to results estimated post-merger based on 100 bootstrap samples. Across the samples, the predicted WTP for HMO and PPO patients are 4.47% higher than the post-merger WTP. Thus, the model seems to be quite stable across time, providing some evidence that analysis conducted before the merger occurs may give insight about the mergers effects.[28]

3.3. **Empirical Results from the Long Island Merger.** We apply the same methodology to analyze the Long Island merger case.[29] Here, we report empirical results addressing the reliability of the model's out-of-sample WTP prediction, $\widehat{WTP}$, from pre-merger data.

Using data drawn from public sources,[30] we again use empirical estimates of the logit model to predict $\widehat{WTP}$, the WTP with pre-merger 1996 data.[31] Next, we use the 1999 post-merger data to re-estimate the model and use the new coefficient estimates to compute $\widetilde{WTP}$, the estimated post-merger WTP in 1999. Bootstrap methods on 100 pseudo-samples are used to analyze the empirical distribution of the difference of the two WTPs. As in the previous analysis, we first conduct the prediction using all patients in the data, i.e. patients with Medicare, Medicare HMO, Blue Cross, commercial HMO or commercial fee-for-service insurance including observations on emergency admissions. These results are summarized in table 6. Before the merger, the two hospitals had a combined WTP of 60310 in 1996 and the predicted post-merger WTP was 75552; that amounts to an increase of about 25% in WTP if the merger were allowed. The post-merger WTP in 1999 was 77065 after adjusting patient volume. On average, the predicted post-merger WTP is a mere 2% different from the predicted post-merger $\widetilde{WTP}$.

A final set of predictions were conducted using the previous strategy of fitting the logit model using observations only on Medicare, commercial insurance, HMO, and PPO patients who were non-emergency admissions to obtain the parameters of the choice model. These estimates

[28]In an expanded sample constructed to test robustness and reported in the appendix, the predicted WTP is 8.67% lower than the post-merger WTP.

[29]The separate appendix discusses various sample construction issues, including the selection of hospitals and patients and other properties of the sample.

[30]Inpatient discharge data are taken from Healthcare Cost and Utilization Project (HCUP). These data include information on the variables T_ij and X_i. Hospital financial variables, H_j are collected from AHA Guide to Health Care Field and Hospital Cost Report from Center for Medicare and Medicaid Services. Summary statistics are provided in the appendix.

[31]For the sake of brevity, we omit reporting the estimated parameters from the model. These results are available upon request from the authors.

form the basis of the predictions on WTP for observations on the remaining, commercial HMO and PPO patient observations, and are reported in table 7. The results show rather large predicted changes in WTP from the pre-merger data, and indeed, these predictions match the post-merger results quite accurately. Thus, the results confirm, qualitatively, the interpretation provided from the full sample.

In sum, the analysis from the Long Island merger provides some support for the position that these choice model approaches may have good predictive accuracy. It is interesting to compare our results with the changes in HHI determined by patient flow criteria. Queens and Nassau Counties were considered by both parties as the relevant geography, however, the government argued that the two merging hospitals were "anchor" hospitals and competed only against each other, while the defendants argued for the inclusion of all hospitals located in the two counties. If we adopt the defendants position, LIFO = (Local Consumption from Local Supply)/(Local Consumption) = 92% and LOFI = (Local Consumption from Local Supply)/(Local Production)=81%. Based on discharges for the hospitals in these counties, the pre-merger HHI = 567.8574 and the post-merger HHI = 800.8434. Under prevailing guidelines, a merger of this magnitude would be unlikely to cause adverse competitive effects in the market. In contrast, we find the price effects are likely to be substantial, indicating a change in the WTP in excess of 20%.

4. Conclusions

The value of obtaining estimates of willingness-to-pay (WTP) based on empirical analysis of demand is shown clearly in our bargaining analysis. While the structure is simplified, the results of bargaining in the option demand framework lead to a close correspondence between rates paid to hospitals and the aggregate WTP. Co-located mergers provide hospitals with extra bargaining power in contracts with MCOs and the resulting effects on prices are proportionate to the change in WTP implied by the joint ownership.

Our empirical results lead to two conclusions. First, both mergers in our study were likely to create a sizeable change in WTP, not because there are insufficient numbers of hospitals in the geographic areas, but because many patients residing within faced a more limited set of choices than the set of all hospitals identified by the traditional methods. Second, the empirical approach, when taken prospectively to construct WTP estimates from pre-merger analysis, is reasonably accurate when compared against the results obtained from the post-merger data. The predicted changes may be judged accurate enough to suit preliminary investigations about the likely impacts of hospital mergers on local consumers in situations where choice constraints are highly localized in the affected metropolitan area.

The Long Island merger is a particularly pertinent example of the geographic problem facing antitrust authorities. During the investigation, DOJ argued that the merger would violate the merger guidelines and significantly increase the two hospitals' joint market power. But the court ruled in favor of the merger because of the parties' not-for-profit status and the high volume of patient flows across a broad area. Our results show that on average the predicted post-merger WTP for all patients would have raised concerns about this merger. Moreover, the pre-merger prediction is about 2% below the actual post-merger WTP. If we exclude emergency admissions and focus on patients with HMO and commercial insurance, the prediction error is only 1.05%.

It would be constructive to find an alternative method to define hospital market that is consistent with consumer choice theory and provide a stronger foundation for merger analysis. The willingness-to-pay (WTP) methodology provides a promising alternative. The idea itself is not new. McFadden (1994) used the WTP to evaluate the value of preserving wilderness areas in western United States. Green et al. (1995) compared the WTP method with Contingent Valuation using an experiment on paying for public goods. McFadden (1998) used similar method to measure the public's willingness-to-pay for public transportation improvement. The patient discharge data sets and financial data required for this method are uniform and widely available in many states, so it should be feasible to incorporate this kind of analysis when circumstances require it. This study recommends further research concerning how well the new approach can predict the impact of a merger, and whether the prediction is reliable.

Table 1. Variables Used in the Model

Variable	Definition
Rj	NFP, FP, Gov: dummy indicating a hospital's type of control; Not-For-Profit (NFP), For-Profit (FP), Government Hospital (Gov)
	Teaching: dummy indicating whether a hospital is a teaching hospital.
	nurse_int : nursing intensity: nursing hours divided by patient days
	capital intensity: dollar value of capital asset divided by inpatient days, (include land, land improvement, buildings, fixed equipment, leasehold improvement, movable equipment, construction in progress)
	h_transplant: dummy variable for transplant services
Sj(dummy)	h_nerv:dummy variable indicating whether the hospital specializes in the disease of nervous system
	h_resp:respiratory
	h_cardio: cardiac care
	h_labor: labor and delivery
	h_mri: magnetic resonance imaging
	h_psych: psychiatric care
Xi	admission: type of admission: 1. Emergency 2. Urgent 3. Elective 4. Newborn 5. Other Male: indicating gender White: indicating race Age: patient age at admission elderly: indicating whether the patient is over 60 child: indicating whether the patient is under 17 income1994: calculated from 1990 and 2000 Census, based on zip codes and race lstay: length of stay ndx: number of other procedures npx: number of other diagnoses xchrlson: Charlson Index (instead of using pcctravel)
	cardio: dummy variable indicating whether the patient has cardio disease labor: labor and delivery resp: respiratory disease digest: disease and disorders of the digestive system muscl: disease and disorders of the musculoskeletal system and connection tissue
	nerv: diseases and disorders of the nervous system urinary: diseases and disorders of the kidney and urinary tract genital: diseases and disorders of reproductive system psych: mental diseases and disorders liver: diseases and disorders of the hepatobiliary system and pancreas
	endor: endocrine, nutritional and metabolic diseases and disorders infection: infectious and parasitic diseases integ:diseases and disorders of the skin, subcutaneous tissue and breast myelop: myeloproliferative disorders injury: injuries, poisonings and toxic effects of drugs
	ent: diseases and disorders of the ear, nose and throat image:magnetic resonance imaging other: diseases and disorders of the eye,burns, alcohol/drug use and alcohol/drug induced organic mental disorders factors influencing health status and other contacts with health services
Time	t: travel time for patient i to hospital j
Distance	travel distance between patients and hospitals
Insurance:	medicare: patient insured by Medicare medicarhm: patient insured by Medicare-HMO blue cross:patient insured by blue cross commins: patient insured by commercial insurance commhmo: patient insured by Commercial HMO commppo: Commercial PPO

Table 2. Patient Sample Statistics in Florida Merger Case in 1994 and 1997

	Premerger 1994				Postmerger 1997			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
nfp	0.597	0.491	0	1	0.424	0.494	0	1
fp	0.381	0.486	0	1	0.557	0.497	0	1
teaching	0.000	0.000	0	0	0.001	0.031	0	1
nurse_int	0.062	0.017	0.045	0.125	0.064	0.022	0.036	0.164
cap_int	0.807	0.282	0.109	1.655	0.961	0.404	0.436	1.809
h_transplant	0.002	0.045	0	1	0.001	0.031	0	1
h_resp	1.000	0.000	1	1	1.000	0.000	1	1
h_cardio	0.806	0.396	0	1	0.831	0.375	0	1
h_labor	0.664	0.472	0	1	0.652	0.476	0	1
h_mri	0.748	0.434	0	1	0.902	0.297	0	1
h_psych	0.314	0.464	0	1	0.301	0.459	0	1
admission	1.931	0.929	1	5	1.961	0.928	1	5
male	0.442	0.497	0	1	0.444	0.497	0	1
white	0.839	0.367	0	1	0.841	0.365	0	1
age	59.072	26.391	0	99	59.848	26.431	0	99
elderly	0.632	0.482	0	1	0.635	0.481	0	1
child	0.102	0.302	0	1	0.102	0.303	0	1
income	23.192	12.279	5.534	92.646	24.298	12.413	0	94.544
lstay	5.346	5.862	1	202	4.788	5.224	1	367
ndx	4.399	2.856	0	9	4.556	2.867	0	9
npx	0.773	1.482	0	9	0.769	1.473	0	9
xchrlson	2.930	2.306	0	14	2.953	2.257	0	14
cardio	0.249	0.432	0	1	0.247	0.431	0	1
labor	0.138	0.345	0	1	0.128	0.334	0	1
resp	0.098	0.298	0	1	0.104	0.305	0	1
digest	0.096	0.294	0	1	0.093	0.290	0	1
muscl	0.084	0.278	0	1	0.084	0.277	0	1
nerv	0.069	0.254	0	1	0.073	0.261	0	1
urinary	0.033	0.180	0	1	0.033	0.178	0	1
genital	0.042	0.202	0	1	0.036	0.186	0	1
psych	0.024	0.152	0	1	0.036	0.186	0	1
liver	0.027	0.162	0	1	0.026	0.160	0	1
endor	0.028	0.166	0	1	0.029	0.169	0	1
infection	0.024	0.154	0	1	0.030	0.170	0	1
integ	0.021	0.145	0	1	0.019	0.137	0	1
myelop	0.019	0.137	0	1	0.017	0.131	0	1
injury	0.010	0.100	0	1	0.009	0.094	0	1
ent	0.009	0.093	0	1	0.008	0.090	0	1
image	0.031	0.172	0	1	0.036	0.186	0	1
other	0.027	0.162	0	1	0.027	0.161	0	1
time	11.961	11.216	0	102	12.332	10.570	0	102
distance	7.482	8.275	0	75	7.706	7.812	0	75
medicare	0.472	0.499	0	1	0.411	0.492	0	1
medcarhm	0.054	0.226	0	1	0.136	0.343	0	1
commins	0.130	0.337	0	1	0.069	0.254	0	1
commhmo	0.169	0.374	0	1	0.236	0.424	0	1
commppo	0.175	0.380	0	1	0.148	0.355	0	1
N. of Obs.	63992				76455			

Note: variables are defined in table 1.

Table 3. Estimation Results from the Florida Merger Case.

Variable	Coeff.	Std. Err.	Variable	Coeff.	Std. Err.
fp	-1.094††	0.058	h_labor	-0.304††	0.017
fp*male	0.173††	0.018	h_lab*labor	6.608††	0.379
fp*white	0.225††	0.032	h_mri	-0.306††	0.019
fp*elderly	0.315††	0.045	h_mri*image	0.466††	0.065
fp*child	-0.061	0.053	h_psych	0.335††	0.018
fp*age	0.016††	0.001	h_psy*psych	3.402††	0.105
fp*income1994	0.004††	0.001	time	-0.068††	0.005
fp*lstay	0.000	0.002	t*fp	-0.003‡	0.001
fp*ndx	-0.083††	0.004	t*nurse_int93	0.906††	0.037
fp*npx	0.013‡	0.007	t*cap_int93	0.044††	0.002
fp*xchrlson	-0.070††	0.006	t*male	0.000	0.001
nurse_int93	-15.829††	1.764	t*white	-0.007††	0.002
nurse*male	-1.288‡	0.593	t*elderly	-0.013††	0.003
nurse*white	3.062††	0.982	t*child	-0.028††	0.003
nurse*elderly	-3.155‡	1.416	t*age	-0.002††	0.000
nurse*child	-3.385‡	1.530	t*income1994	-0.001††	0.000
nurse*age	-0.300††	0.034	t*lstay	0.000‡	0.000
nurse*income	0.382††	0.049	t*ndx	0.000	0.000
nurse*lstay	-0.494††	0.065	t*npx	0.007††	0.000
nurse*ndx	2.783††	0.131	t*xchrlson	0.005††	0.000
nurse*npx	-0.311	0.214	t*cardio	-0.017††	0.003
nurse*xchrlsonn	0.353†	0.193	t*labor	-0.016††	0.003
cap_int93	-0.633††	0.114	t*resp	-0.02††	0.003
cap*male	0.007	0.039	t*digest	-0.019††	0.003
cap*white	-0.481††	0.060	t*muscl	0.005	0.003
cap*elderly	-0.302††	0.089	t*nerv	-0.019††	0.004
cap*child	-0.028	0.098	t*urinary	-0.006	0.004
cap*age	0.017††	0.002	t*genital	0.012††	0.004
cap*income	0.001	0.003	t*psych	0.021††	0.006
cap*lstay	-0.013††	0.004	t*liver	-0.022††	0.004
cap*ndx	-0.003	0.009	t*endor	-0.013††	0.004
cap*npx	-0.287††	0.015	t*infection	-0.01‡	0.004
cap*xchrlson	0.090††	0.013	t*integ	-0.009†	0.005
h_transplant	2.163††	0.121	t*myelop	0.017††	0.005
h_nerv	-0.525††	0.026	t*injury	-0.008	0.005
h_nerv*nerv	0.081	0.063	t*ent	-0.002	0.005
h_cardio	0.508††	0.028	t*image	0.004	0.003
h_car*cardio	0.337††	0.030			

†† p-value .01 or less; ‡ p-value .05 or less and † p-value .1 or less
Number of obs = 473466
LR chi2(75) = 60454.42
Prob ¿ chi2 = 0.000
Pseudo R2 = 0.240
Log likelihood = -95648.548

Table 4. Effects on WTP of the Florida Merger Case

	Premerger			Postmerger		
Bootstrap	WTP merged 1994 data	WTP separate 1994 data	predicted change, %	WTP merged 1997 data	97-94 chg, %	prediction error, %
1	32011	25841	23.87	31041	20.12	3.03
2	32644	26253	24.34	30882	17.63	5.40
3	33191	26669	24.45	31466	17.99	5.20
4	32386	26147	23.86	30798	17.79	4.90
5	32382	26065	24.24	31222	19.79	3.58
6	32551	26172	24.37	31419	20.04	3.48
7	32334	26062	24.06	31076	19.24	3.89
8	32959	26488	24.43	30758	16.12	6.68
9	32492	26208	23.98	31090	18.63	4.31
10	32603	26203	24.43	31566	20.47	3.18
-	-	-	-	-	-	-
100	32365	26109	23.96	31382	20.20	3.04
Mean, all 100	32499	26205	**24.02**	31230	**19.18**	**3.90**
St. Dev	238.28	158.71	**0.22**	241.54	**1.16**	**1.01**

Table 5. Effects on WTP of the Florida Merger Case for HMO and PPO Patients (Emergency Admissions Excluded)

	Premerger			Postmerger		
	WTP merged 1994 data	WTP separate 1994 data	predicted change, %	WTP merged 1997 data	97-94 chg, %	prediction error, %
1	4926.84	4251.89	15.87	4679.32	10.05	5.02
2	4902.50	4225.69	16.02	4674.98	10.63	4.64
3	4884.58	4211.17	15.99	4722.46	12.14	3.32
4	4937.10	4264.86	15.76	4753.44	11.46	3.72
5	4895.85	4233.09	15.66	4737.08	11.91	3.24
6	5042.16	4345.70	16.03	4647.43	6.94	7.83
7	4934.35	4248.34	16.15	4795.23	12.87	2.82
8	4870.56	4208.82	15.72	4698.84	11.64	3.53
9	5005.16	4311.64	16.08	4739.08	9.91	5.32
10	5060.74	4338.47	16.65	4738.49	9.22	6.37
100	4831.35	4175.43	15.71	4733.54	13.37	2.02
Mean, all 100	4936.14	4257.55	**15.94**	4714.28	**10.75**	**4.47**
St. Dev	74.37	59.74	**0.21**	53.84	**1.94**	**1.74**

Table 6. Merger Effects on WTP of the Long Island Merger Case

	Premerger			Postmerger		
	WTP merged 1996 data	WTP separate 1996 data	predicted change, %	WTP merged 1999 data	99-96 chg, %	prediction error, %
1	75050.79	60133.69	24.81	76586.61	27.36	2.05
2	75472.76	60280.07	25.20	76747.95	27.32	1.69
3	75269.97	60027.30	25.39	76955.08	28.20	2.24
4	75664.98	60491.53	25.08	76952.70	27.21	1.70
5	75686.00	60246.48	25.63	77033.69	27.86	1.78
6	75764.84	60364.78	25.51	77372.72	28.18	2.12
7	75548.58	60329.90	25.23	77557.18	28.56	2.66
8	75948.16	60527.92	25.48	76709.77	26.73	1.00
9	74860.22	59921.97	24.93	77206.97	28.85	3.13
10	75972.28	60569.13	25.43	76761.76	26.73	1.04
-	-	-	-	-	-	-
100	75317.68	60052.65	25.42	77540.23	29.12	2.95
Mean, all 100	75551.76	60310.06	**25.27**	77065.36	**27.78**	**2.01**
St. Dev	358.42	234.84	**0.18**	294.32	**0.71**	**0.63**

Table 7. Effects on WTP of the NY Merger Case for HMO and Commercial Insurance Patients(Emergency Admissions Excluded)

	Premerger			Postmerger		
	WTP merged 1996 data	WTP separate 1996 data	predicted change, %	WTP merged 1999 data	99-96 chg, %	prediction error, %
1	24562.06	19925.97	23.27	24731.13	24.12	0.69
2	24788.79	20070.36	23.51	24799.34	23.56	0.04
3	24496.97	19815.40	23.63	24926.80	25.80	1.75
4	24696.06	20025.26	23.32	24892.78	24.31	0.80
5	24817.43	20006.61	24.05	25287.86	26.40	1.90
6	24810.82	20065.65	23.65	25144.26	25.31	1.34
7	24735.88	19972.88	23.85	25188.09	26.11	1.83
8	24874.64	20149.93	23.45	24793.94	23.05	-0.32
9	24319.06	19735.26	23.23	24849.47	25.91	2.18
10	24815.94	20038.09	23.84	25037.84	24.95	0.89
-	-	-	-	-	-	-
100	24713.41	20011.78	23.49	25197.42	25.91	1.96
Mean, all 100	24692.78	20012.09	**23.39**	24950.84	**24.68**	**1.05**
St. Dev	206.38	130.77	**0.60**	224.15	**1.43**	**1.28**

Empirical Documentation to accompany "What does willingness-to-pay reveal about hospital market power in merger cases?"

In this document, we describe in detail how samples where constructed from the patient discharge data for each of three samples. While the discharge databases contain complete records of all patient discharges from acute care hospitals, sampling is necessary to implement the empirical choice model to satisfy computational constraints. Further, we investigate how the results change when we increase sample size, i.e. include many more patients and hospitals in the model. We find that the model obtains similar results under alternative sampling frames, although the error rates are somewhat higher (up to 9% error rates) as the sample is expanded. Finally, the construction of the sample for the Long Island merger analysis is discusses.

1.1. **Sample Construction for the Palm Beach, Florida analysis.** Table 8 reports the coverage rates, i.e. the percent of the hospital's total discharges included in the final sample for 1994, for patients from the 33 zip codes. As an example, there are in total 3493 patients from zip code 33401 receiving service from 55 hospitals. After excluding hospitals with less than 50 patients for 1994, there are 3258 patients remaining, comprising about 93% of all the patients from zip code 33401. In the total sample, we account for 90113 patients, over 92% of total patients. We will call this sample the "n-4 sample" for purposes of comparison below, because it contains essentially the complete patient population in the areas where the four focal hospitals compete, shown in table 9 in boldface red for those with the colorized copy of this document, whereas the coverage rates for the other 16 peripheral hospitals are relatively low. Similar patient choice sets are constructed for the 1997 post-merger data.

We construct choice sets by assuming that all patients in a given zip code face a fixed set of alternative hospitals and we infer that set from the consumption patterns observed in the discharge data. For example, from zip code 33401, about 95% of the patients went to 6 of the 20 hospitals, each of which accepted more than 50 patients. In this manner, we determined that patients from zip code 33401, for example, have 6 alternatives in their choice set. Each patient's choice set from the 33 zip codes can be defined similarly. Every patient has at least one and at most 4 of the merged hospitals in their choice set. Even with only one, a patient could be affected by the merger since MCO contracts with the merged hospitals are likely to be aggregated over all members and

Table 8. Total Number of Patients and Percentage Coverage, by Zip Code, in the n-4 Sample

Zip Code	Total Patients	Patients After Exclusions	Percent Coverage
33401	3493	3258	0.933
33403	1388	1285	0.926
33404	4592	4338	0.945
33405	2380	2206	0.927
33406	2410	2278	0.945
33407	4513	4132	0.916
33408	2072	1920	0.927
33409	2289	2075	0.907
33410	2995	2775	0.927
33411	3837	3570	0.930
33413	597	447	0.749
33414	2495	2289	0.917
33415	4697	4475	0.953
33417	4377	4184	0.956
33418	1902	1726	0.907
33426	1523	1268	0.833
33430	3928	3692	0.940
33435	4695	4383	0.934
33436	3096	2791	0.901
33437	2931	2566	0.875
33440	2397	2074	0.865
33445	3867	3491	0.903
33458	2507	2361	0.942
33460	4051	3828	0.945
33461	4030	3790	0.940
33462	3905	3526	0.903
33463	3697	3493	0.945
33467	3243	2891	0.891
33470	1087	885	0.814
33476	1778	1626	0.915
33480	1642	1427	0.869
33484	4875	4544	0.932
33493	617	519	0.841
Total	97906	90113	0.920

Table 9. Total Number of Patients and Percentage Coverage, by hospital, in n-4 Sample for 1994

ID	Hospital Name	City	County	Total N	N in Sample	percent
100002	BETHESDA MEMORIAL	Boynton Beach	Palm Beach	14086	9936	70.54
100010	SAINT MARY'SHOSPITAL	West Palm Beach	Palm Beach	21659	19308	89.15
100012	LEE MEMORIAL HOSPITAL	Fort Myers	Lee	24709	211	0.85
100080	**JFK MEDICAL CENTER**	Atlantis	Palm Beach	12168	10805	88.80
100098	HENDRY REGIONAL	Clewiston	Hendry	1144	795	69.49
100130	GLADES GENERAL HOSPITAL	Belle Glade	Palm Beach	3186	2954	92.72
100144	EVERGLADES REGIONAL	Pahokee	Palm Beach	2898	2471	85.27
100168	BOCA RATONCOMMUNITY	Boca Raton	Palm Beach	15342	1772	11.55
100176	PALM BEACH GARDENS	Palm Beach Gardens	Palm Beach	8589	6067	70.64
100199	POMPANO BEACH MEDICAL	Pompano Beach	Broward	5858	157	2.68
100207	**PALM BEACH REGIONAL**	Lake Worth	Palm Beach	5132	4738	92.32
100220	SOUTHWEST FLORIDA	Fort Myers	Lee	11510	100	0.87
100234	**COLUMBIA HOSPITAL**	West Palm Beach	Palm Beach	5131	4382	85.40
100237	NORTH RIDGE MEDICAL	Ft.Lauderdale	Broward	7219	225	3.12
100253	JUPITER MEDICAL CENTER	Jupiter	Palm Beach	5602	2050	36.59
100258	DELRAY MEDICAL CENTER	Delray Beach	Palm Beach	10359	6070	58.60
110006	**PALMS WEST HOSPITAL**	Loxahatchee	Palm Beach	4945	4302	87.00
110008	WEST BOCA MEDICAL	Boca Raton	Palm Beach	9440	627	6.64
110010	WELLINGTON REGIONAL	Wellington	Palm Beach	3000	2232	74.40
110403	GOOD SAMARITAN HOSPITAL	West Palm Beach	Palm Beach	12445	10852	87.20

networks do not vary access to hospitals by zip code. The number of hospitals in the resulting choice sets range from 3 to 10.

Among the 20 acute care hospitals, 15 are in Palm Beach County, 2 in the adjacent Broward, 2 in Lee County, 1 in the adjacent Henry County.

The 15 included hospitals in Palm Beach County constitute all acute-care hospitals in the county. Of the 90113 total patients, over 98% of them (88566) went to one of the 16 hospitals in Palm Beach County. Hospital ownership and service provision are listed in table 10.

TABLE 10. Hospital Control Type and Services Offered in the Florida Sample

Hospital Name	Control	mri	cardio	nerv	resp	labor	psych	transplant
BETHESDA MEMORIAL HOSPITAL	NFP	1	1	1	1	1	1	0
SAINT MARY'S HOSPITAL	NFP	1	1	1	1	1	1	0
LEE MEMORIAL HOSPITAL	NFP	1	1	1	1	1	0	0
JFK MEDICAL CENTER	NFP	0	1	1	1	0	1	0
HENDRY REGIONAL MEDICAL CENTER	Gov	0	0	0	1	0	0	0
GLADES GENERAL HOSPITAL	Gov	0	0	0	1	1	0	0
EVERGLADES REGIONAL MEDICAL CENTER	NFP	0	1	0	1	1	0	0
BOCA RATON COMMUNITY HOSPITAL	NFP	0	1	0	1	1	0	0
PALM BEACH GARDENS MEDICAL CENTER	FP	1	1	1	1	1	0	0
POMPANO BEACH MEDICAL CENTER	FP	0	1	1	1	0	0	0
PALM BEACH REGIONAL HOSPITAL	FP	1	1	1	1	1	0	0
SOUTHWEST FLORIDA REGIONAL	FP	1	1	1	1	0	0	1
COLUMBIA HOSPITAL	FP	0	0	1	1	0	1	0
NORTH RIDGE MEDICAL CENTER	FP	1	1	1	1	0	0	0
JUPITER MEDICAL CENTER	NFP	1	0	0	1	0	0	0
DELRAY MEDICAL CENTER	FP	0	1	1	1	0	0	0
PALMS WEST HOSPITAL	FP	0	0	1	1	1	0	0
WEST BOCA MEDICAL CENTER	FP	0	0	0	1	1	0	0
WELLINGTON REGIONAL MEDICAL CENTER	FP	1	0	1	1	1	0	0
GOOD SAMARITAN HOSPITAL	NFP	1	1	1	1	1	0	0

Note: Control indicates Not-for-Profit (NFP), Government (Gov) or for-profit (FP) ownership. The columns indicate whether the hospital offers services or specializes in magnetic resonance imaging (mri), cardiac care (cardio), diseases of nervous system (nerv), respiratory (resp) , labor and delivery (labor), psychiatric care (psych) and organ transplant services (transplant).

1.2. **The Expanded sample to test for robustness.** A question to be addressed here is the sensitivity of the model's predictions to changes in the sampling design. We explore this issue with an expanded sample, the "n-20 Sample". This sample enlarges the coverage of patient discharges (see table 11) to give a comprehensive set of discharges for the merged hospitals as well as the 16 other hospitals who are competing with them.

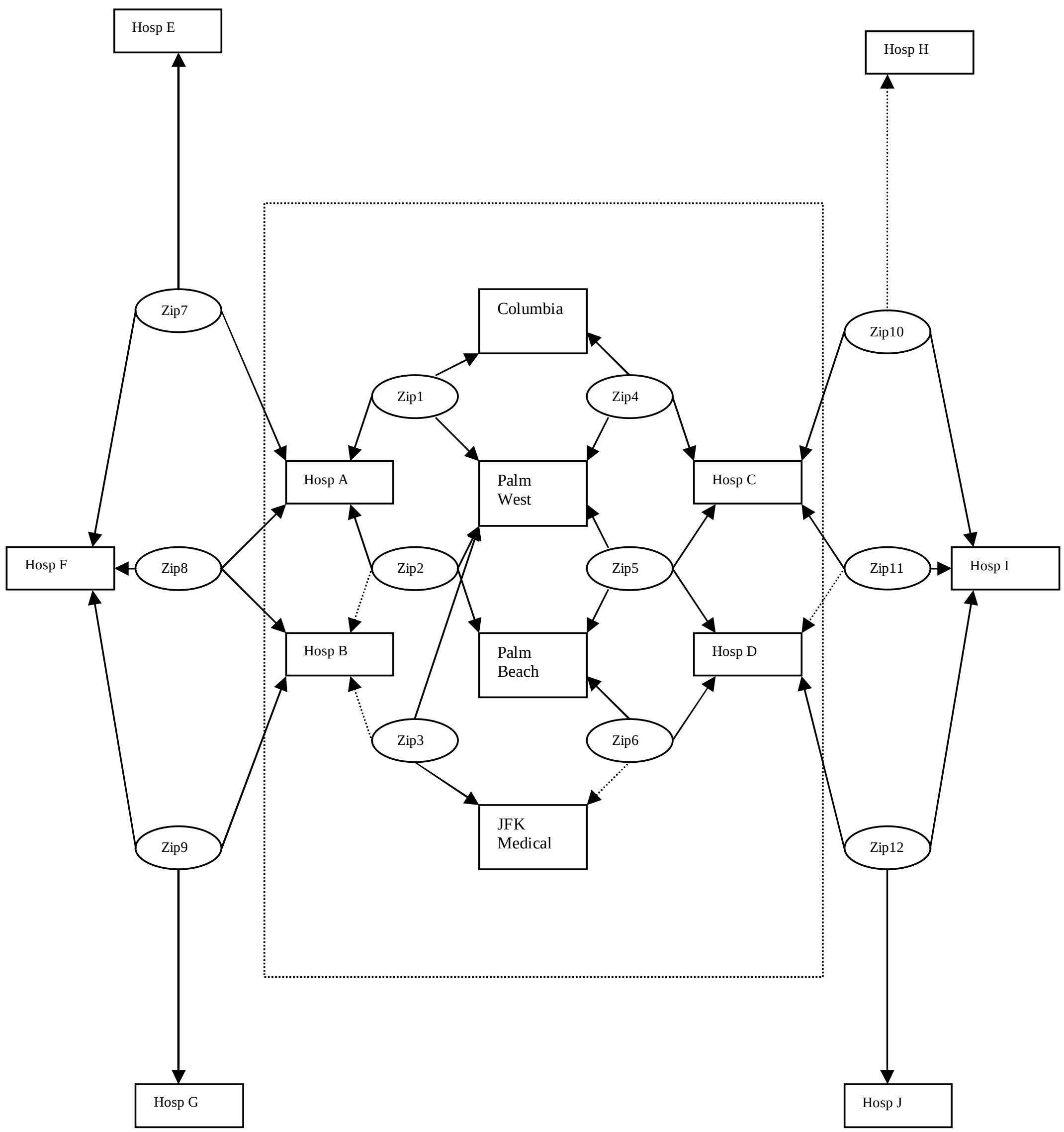

FIGURE 2. hospital market area for the n-20 sample

The expanded sample, illustrated in figure 1.2, contains within it the "n-4" sample (shown in the box) but also includes a broader choice set that captures essentially all the patients and zip codes that are relevant to the 16 peripheral hospitals. In this "n-20 Sample", there are 81 additional hospitals that have to be included to construct complete choice sets for the additional zip codes.

Note, finally that for 1997 there are only 3 merged hospitals remaining (one having been closed) and 15 peripheral hospitals.

TABLE 11. Percentage Coverage in n-20 Sample in Florida for 1994

Hosp ID	Hospital Name	Total Number of Patients	Number of Patients in Sample	Coverage Rate(%)
100002	BETHESDA MEMORIAL	14086	13165	93.46
100010	SAINT MARY'SHOSPITAL	21659	20244	93.47
100012	LEE MEMORIAL HOSPITAL	24709	22493	91.03
100080	**JFK MEDICAL CENTER**	12168	10805	88.80
100098	HENDRY REGIONAL	1144	1001	87.50
100130	GLADES GENERAL HOSPITA	3186	3040	95.42
100144	EVERGLADES REGIONAL	2898	2719	93.82
100168	BOCA RATONCOMMUNITY	15342	13379	87.21
100176	PALM BEACH GARDENS	8589	7517	87.52
100199	POMPANO BEACH MEDICAL	5858	5256	89.72
100207	**PALM BEACH REGIONAL**	5132	4738	92.32
100220	SOUTHWEST FLORIDA	11510	10231	88.89
100234	**COLUMBIA HOSPITAL**	5131	4382	85.40
100237	NORTH RIDGE MEDICAL	7219	6147	85.15
100253	JUPITER MEDICAL CENTER	5602	4590	81.94
100258	DELRAY MEDICAL CENTER	10359	9521	91.91
110006	**PALMS WEST HOSPITAL**	4945	4302	87.00
110008	WEST BOCA MEDICAL	9440	8463	89.65
110010	WELLINGTON REGIONAL	3000	2232	74.40
110403	GOOD SAMARITAN HOSPITAL	12445	11131	89.44

Note that the patient choice sets in the earlier "n-4" sample (those patients and hospitals in the box) remain identical in the "n-20" sample because that is determined uniquely for each zip code, and the zip codes relevant to the 4 merging hospitals has the same set of hospitals in both samples.

1.3. **Bootstrap Predictions Based on the "n-20 Sample".** In the paper, we presented bootstrap results for predictions of the model based on the "n-4" sample. To examine the robustness of these results, a further set of predictions from a new set of conditional logit models was estimated on 100 pseudo-samples based upon the "n-20" sample.

Recall that the analysis of the "n-4 sample" focused on four hospitals that were subject to merger. As shown in table 9, the sample covers over 85% of discharges from the four hospitals. But for the other 16 hospital the coverage rate is relatively low. In the "n-20" sample we are able to assess the aggregate WTP for all of the 20 hospitals, instead of only the limited ones who were merging because the "n-20" sample covers a large percent of patients for all 20 hospitals (see table 11).

Table **??** compares the estimation results of the logit model using n-4 and n-20 sample. The results from the expanded sample in table 12 yield somewhat less precise forecasts than the 3.9% average error rate obtained from the predictions using the "n-4" sample. Looking at the pre-merger prediction of the WTP relative to the actual post-merger WTP from 1997, the mean error of the model based on the 1994 data is 4.79%. Moreover, table 13 reports additional predictions from models estimated on bootstrap samples excluding patient records for emergency admissions. In the table, the prediction error is -8.67%, somewhat larger than the 4.47% error obtained in the equivalent predictions from the "n-4" sample. Thus the model under-predicts market power effects in this case. In general, the larger "n-20" sample provides some additional statistical efficiency in the coefficient estimates of the model, but would produce more volatile estimates of the effects if the hospital service profiles are quite different and patient preferences over hospital attributes varies as the breadth of the market grows. For example, with the "n-20" sample there are 81 hospitals instead of only 20 in the "n-4" sample. Thus, if the marginal value of hospital service is lower in the expanded sample, that would affect the conditional logit estimates and may result in a higher prediction error.

TABLE 12. Effects on WTP of the Florida Merger Case in "n-20" Sample

	Premerger			Postmerger		
	WTP merged 1994 data	WTP separate 1994 data	predicted change, %	WTP merged 1997 data	97-94 chg, %	prediction error, %
1	28435.45	23479.04	21.11	27348.49	16.48	3.82
2	28867.88	23782.73	21.38	27207.71	14.40	5.75
3	28661.27	23658.04	21.15	27385.88	15.76	4.45
4	28776.14	23710.39	21.37	27351.76	15.36	4.95
5	28763.86	23689.19	21.42	27193.94	14.79	5.46
6	28666.50	23628.82	21.32	27282.49	15.46	4.83
7	28869.29	23827.92	21.16	27396.10	14.97	5.10
8	28562.88	23536.49	21.36	27714.79	17.75	2.97
9	28887.95	23770.25	21.53	27508.51	15.73	4.78
10	28893.63	23792.02	21.44	27122.01	14.00	6.13
-	-	-	-	-	-	-
100	28921.92	23817.20	21.43	27511.65	15.51	4.88
Mean, all 100	28714.37	23671.30	21.30	27336.97	15.49	4.79
St. Dev	230.24	166.23	0.16	179.69	1.09	0.97

TABLE 13. Effects on WTP of Florida Merger Case in "n-20" Sample (for HMO and PPO Patients, Emergency Admissions Excluded)

	Premerger			Postmerger		
	WTP merged 1994 data	WTP separate 1994 data	predicted change, %	WTP merged 1997 data	97-94 chg, %	prediction error, %
1	4995.78	4334.80	15.25	5412.12	24.85	-8.33
2	5114.19	4433.08	15.36	5406.32	21.95	-5.71
3	4896.62	4254.88	15.08	5388.73	26.65	-10.05
4	5057.44	4389.72	15.21	5420.70	23.49	-7.18
5	5024.30	4371.97	14.92	5442.10	24.48	-8.32
6	5034.60	4373.42	15.12	5442.32	24.44	-8.10
7	4947.38	4299.55	15.07	5437.22	26.46	-9.90
8	5032.74	4378.33	14.95	5493.46	25.47	-9.15
9	4951.17	4306.66	14.97	5468.65	26.98	-10.45
10	5033.21	4366.39	15.27	5400.47	23.68	-7.30
100	4907.67	4269.30	14.95	5531.60	29.57	-12.71
Mean, all 100	5004.39	4347.34	15.11	5437.17	25.09	-8.67
St. Dev	65.23	51.81	0.18	51.62	1.83	1.69

Table 14. Estimation Results from "n-4" Sample and "n-20" Sample.

	n-4 Sample:		n-20 Sample:	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
fp	-1.094††	0.058	-0.415††	0.029
fpmale	0.173††	0.018	0.079††	0.010
fpwhite	0.225††	0.032	0.028	0.017
fpelderly	0.315††	0.045	0.238††	0.023
fpchild	-0.061	0.053	0.215††	0.028
fpage	0.016††	0.001	0.013††	0.001
fpincome1994	0.004††	0.001	-0.018††	0.001
fplstay	0.000	0.002	0.010††	0.001
fpndx	-0.083††	0.004	-0.151††	0.002
fpnpx	0.013‡	0.007	0.018††	0.004
fpxchrlson	-0.070††	0.006	-0.013††	0.003
nurse_int93	-15.829††	1.764	-21.543††	1.190
nursemale	-1.288‡	0.593	-0.161	0.426
nursewhite	3.062††	0.982	-1.623‡	0.672
nurseelderly	-3.155‡	1.416	1.467	1.010
nursechild	-3.385‡	1.530	-9.428††	1.126
nurseage	-0.300††	0.034	-0.299††	0.025
nursein 1994	0.382††	0.049	0.479††	0.029
nurselstay	-0.494††	0.065	-0.938††	0.045
nursendx	2.783††	0.131	1.096††	0.096
nursenpx	-0.311	0.214	0.920††	0.161
nursexchrl n	0.353†	0.193	0.320‡	0.142
cap_int93	-0.633††	0.114	-0.965††	0.061
capmale	0.007	0.039	-0.122††	0.021
capwhite	-0.481††	0.060	-0.002	0.035
capelderly	-0.302††	0.089	-0.292††	0.049
capchild	-0.028	0.098	-0.010	0.056
capage	0.017††	0.002	0.004††	0.001
capinco 1994	0.001	0.003	0.005††	0.002
caplstay	-0.013††	0.004	-0.005‡	0.002
capndx	-0.003	0.009	-0.028††	0.005
capnpx	-0.287††	0.015	-0.193††	0.008
capxchrlson	0.090††	0.013	0.066††	0.007
h_transplant	2.163††	0.121	0.232††	0.015
h_nerv	-0.525††	0.026	-0.263††	0.009
h_nervnerv	0.081	0.063	0.134††	0.027
h_cardio	0.508††	0.028	0.317††	0.009
h_carcardio	0.337††	0.030	0.291††	0.016

	n-4 Sample:		n-20 Sample:	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.
h_labor	-0.304††	0.017	-0.082††	0.006
h_lablabor	6.608††	0.379	5.753††	0.126
h_mri	-0.306††	0.019	-0.024††	0.007
h_mriimage	0.466††	0.065	-0.134††	0.034
h_psych	0.335††	0.018	-0.199††	0.007
h_psypsych	3.402††	0.105	3.242††	0.054
time	-0.068††	0.005	-0.034††	0.003
tfp	-0.003‡	0.001	0.008††	0.001
tnurse_int93	0.906††	0.037	0.88††	0.018
tcap_int93	0.044††	0.002	0.034††	0.001
tmale	0.000	0.001	0.005††	0.001
twhite	-0.007††	0.002	0.007††	0.001
telderly	-0.013††	0.003	0.01††	0.001
tchild	-0.028††	0.003	-0.040††	0.002
tage	-0.002††	0.000	-0.002††	0.000
tincome1994	-0.001††	0.000	-0.003††	0.000
tlstay	0.000‡	0.000	0.000††	0.000
tndx	0.000	0.000	-0.003††	0.000
tnpx	0.007††	0.000	0.012††	0.000
txchrlson	0.005††	0.000	0.003††	0.000
tcardio	-0.017††	0.003	-0.009††	0.002
tlabor	-0.016††	0.003	-0.026††	0.002
tresp	-0.02††	0.003	-0.033††	0.002
tdigest	-0.019††	0.003	-0.036††	0.002
tmuscl	0.005	0.003	-0.003†	0.002
tnerv	-0.019††	0.004	-0.028††	0.002
turinary	-0.006	0.004	-0.023††	0.002
tgenital	0.012††	0.004	-0.010††	0.002
tpsych	0.021††	0.006	-0.007‡	0.003
tliver	-0.022††	0.004	-0.035††	0.002
tendor	-0.013††	0.004	-0.021††	0.002
tinfection	-0.01‡	0.004	-0.027††	0.003
tinteg	-0.009†	0.005	-0.022††	0.003
tmyelop	0.017††	0.005	0.009††	0.003
tinjury	-0.008	0.005	-0.036††	0.004
tent	-0.002	0.005	-0.022††	0.003
timage	0.004	0.003	-0.009††	0.002

	n-4 Sample	n-20 Sample
Number of obs	473466	1846668
LR chi2(75)	60454.42	222586.4
Prob > chi2	0.000	0
Pseudo R2	0.240	0.2426
Log likelihood	-95648.548	-347428.7

†† p-value .01 or less; ‡ p-value .05 or less and † p-value .1 or less

1.4. **Sample Construction for the Long Island case.** We proceed with the analysis of the Long Island case, using a sampling method similar to the one employed for the Florida case described in section 1.1. Starting with the two hospitals under study: Long Island and North Shore, we find all the zip codes where these hospitals' patients reside. We then include all the other hospitals used by patients from these zip codes.

In selecting patient zip codes from the two merged hospitals, we still require the presence of at least 50 patients for a zip code to be included. Due to higher patient volume in New York than in the Florida case[32], we have 151 zip codes for New York pre-merger compared to only 33 zip codes in Florida. To identify the set of other hospitals that are relevant to patients from these 151 zip codes, we included all hospitals that serve at least 2% of patients from the 151 zip codes. The final data have 59 general short-term acute care hospitals, with 471,980 admissions. Patients in the sample have a maximum of 15 hospitals in their choice sets. Each zip code has on average 80% coverage rate. The data include 91% and 92% of discharges from Long Island and North Shore hospitals respectively. The sample descriptive statistics for the sample are reported in table 15. Finally, each hospital's ownership and range of services they provide are listed in table **??**.

[32]In 1996, the two merged hospitals had 77,835 admissions compared to the total 27,376 admissions of the four merged hospitals in Florida in 1994.

Table 15. Patient Sample Statistics in the New York Merger Case in 1996 and 1999

	Premerger 1996				Postmerger 1999			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
nfp	0.818	0.386	0	1	0.872	0.334	0	1
fp	0.115	0.319	0	1	0.059	0.236	0	1
teaching	0.453	0.498	0	1	0.480	0.500	0	1
nurse_int	0.004	0.001	0.002	0.006	0.004	0.001	0.001	0.008
cap_int	627.655	347.059	142.042	1992.460	826.796	439.287	175.734	2591.921
h_transplant	0.261	0.439	0	1	0.174	0.379	0	1
h_resp	0.988	0.107	0	1	0.970	0.170	0	1
h_cardio	0.614	0.487	0	1	0.627	0.484	0	1
h_labor	0.899	0.301	0	1	0.911	0.284	0	1
h_mri	0.876	0.330	0	1	0.908	0.289	0	1
h_psych	0.787	0.409	0	1	0.805	0.396	0	1
admission	1.842	1.076	1	4	1.780	1.070	1	4
male	0.406	0.491	0	1	0.408	0.491	0	1
white	0.711	0.453	0	1	0.693	0.461	0	1
age	52.461	28.170	0	114	53.103	28.541	0	109
elderly	0.505	0.500	0	1	0.511	0.500	0	1
child	0.147	0.354	0	1	0.150	0.357	0	1
income	25.989	10.503	0	102.562	26.029	10.447	0	102.562
lstay	7.098	11.240	0	835	6.396	9.443	0	354
ndx	3.465	3.044	0	16	3.568	3.113	0	16
npx	1.151	1.926	0	14	1.097	1.862	0	14
xchrlson	2.471	2.349	0	15	2.491	2.312	0	15
cardio	0.197	0.398	0	1	0.204	0.403	0	1
labor	0.211	0.408	0	1	0.207	0.405	0	1
resp	0.100	0.300	0	1	0.106	0.307	0	1
digest	0.090	0.286	0	1	0.091	0.288	0	1
muscl	0.056	0.231	0	1	0.053	0.225	0	1
nerv	0.061	0.239	0	1	0.061	0.240	0	1
urinary	0.039	0.195	0	1	0.039	0.194	0	1
genital	0.035	0.184	0	1	0.033	0.178	0	1
psych	0.026	0.159	0	1	0.026	0.158	0	1
liver	0.031	0.174	0	1	0.028	0.165	0	1
endor	0.030	0.171	0	1	0.035	0.184	0	1
infection	0.021	0.143	0	1	0.023	0.150	0	1
integ	0.025	0.156	0	1	0.024	0.153	0	1
myelop	0.020	0.141	0	1	0.013	0.113	0	1
injury	0.009	0.096	0	1	0.009	0.096	0	1
ent	0.012	0.108	0	1	0.012	0.110	0	1
image	0.021	0.142	0	1	0.030	0.171	0	1
other	0.004	0.062	0	1	0.003	0.052	0	1
time	12.809	8.476	0	48	13.137	8.844	0	54
distance	6.243	5.408	0	39.170	6.477	5.674	0	40.180
medicare	0.434	0.496	0	1	0.403	0.491	0	1
medcarhm	0.024	0.152	0	1	0.046	0.209	0	1
commins	0.168	0.374	0	1	0.139	0.346	0	1
commhmo	0.241	0.428	0	1	0.233	0.423	0	1
commppo	0.133	0.340	0	1	0.178	0.383	0	1
N. of Obs.	297566				321227			

Note: variables are defined in table 1 of the main paper.

Table 16. Hospital Characteristics in the New York Case

Hospital Name	Control	mri	cardio	nerv	resp	labor	psych	transplant
Brunswick General Hospital	FP	1	0	0	1	0	0	0
Southside Hospital	NFP	1	1	1	1	1	1	0
Mid-Island Hospital	FP	0	0	0	1	1	0	0
Brookdale Hospital	NFP	1	1	1	1	1	1	0
Brooklyn Hospital Center	NFP	1	1	1	1	1	0	1
New York Methodist Hospital	NFP	1	1	1	1	1	1	0
Coney Island Hospital	Gov	1	1	1	1	1	1	0
Catholic Medical Center	NFP	1	0	1	1	1	1	0
Interfaith Medical Center	NFP	1	1	1	1	1	1	0
Kingsbrook Jewish Medical Center	NFP	1	0	0	1	0	1	0
Kings County Hospital Center	Gov	1	0	1	1	1	1	0
Kings Highway Hospital Center	FP	1	0	0	1	0	0	0
Long Island College Hospital	NFP	1	1	1	1	1	1	0
New York Comm Hospital	NFP	0	0	0	0	0	0	0
Maimonides Medical Center	NFP	1	1	1	1	1	1	0
University Hospital of Brooklyn-SUNY	Gov	1	1	1	1	1	1	1
Victory Memorial Hospital	NFP	0	0	1	1	1	0	0
Woodhull Medical & Mental Center	Gov	0	0	1	1	1	1	0
Wyckoff Heights Medical Center	NFP	1	0	1	1	1	0	0
St John's Episcopal Hospital	NFP	1	0	1	1	1	1	0
New York Hospital Medical Center	NFP	1	1	1	1	1	1	0
Flushing Hospital Medical Center	NFP	1	0	1	1	1	0	0
North Shore University Flushing	NFP	1	0	1	1	1	0	0
Parkway Hospital	FP	1	0	0	1	0	0	0
North Shore University Glen Cove	NFP	1	0	1	1	1	1	0
Long Island Jewish Medical Center	NFP	1	1	1	1	1	1	1
Hempstead Gen Hospital	FP	0	0	0	0	0	1	0
Nassau County Medical Center	Gov	1	1	1	1	1	1	0
Huntington Hospital	NFP	1	0	1	1	1	1	0
Jamaica Hospital Center	NFP	1	1	1	1	1	1	0
Queens Hospital Center	Gov	1	0	1	1	1	1	0
Long Beach Medical Center	NFP	1	0	0	1	0	1	0
Western Queens Comm Hospital	FP	0	0	1	1	0	0	0
North Shore University Hospital Manhasset	NFP	1	1	1	1	1	1	1
Winthrop-University Hospital	NFP	1	1	1	1	1	1	0
Bellevue Hospital Center	Gov	1	1	1	1	1	1	0
Beth Israel Medical Center	NFP	1	1	1	1	1	1	0
Cabrini Medical Center	NFP	1	0	1	1	0	1	0
New York University Medical Center	NFP	1	1	1	1	1	1	1
Lenox Hill Hospital	NFP	1	1	1	1	1	1	0
Metropolitan Hospital Center	Gov	1	0	1	1	1	1	0
Mount Sinai Medical Center	NFP	1	1	1	1	1	1	1
Elmhurst Hospital Center	Gov	1	1	1	1	1	1	0
Presby Hospital	NFP	1	1	1	1	1	1	1
Saint Vincent's Hospital	NFP	1	1	1	1	1	1	1
Society of the New York Hospital	NFP	1	1	1	1	1	1	1
South Nassau Comms Hospital	NFP	1	1	1	1	1	1	0
Brookhaven Mem Hospital Medical Center	NFP	0	0	1	1	1	1	0
North Shore University Plainview	FP	0	0	1	1	1	1	0
John T Mather Mem Hospital	NFP	1	0	1	1	0	1	0
St Charles Hospital & Rehab Center	NFP	0	0	1	0	1	0	0
Peninsula Hospital Center	NFP	1	0	0	1	0	0	0
Mercy Medical Center	NFP	1	0	1	1	1	1	0
Massapequa General Hospital	FP	0	0	0	1	0	0	0
St John's Episcopal Hospital	NFP	0	1	1	1	1	1	0
University Hospital	Gov	1	1	1	1	1	1	1
North Shore University Syosset	NFP	1	0	0	1	1	1	0
Franklin Hospital Medical Center	NFP	0	0	1	1	1	1	0
Good Samaritan Hospital Medical Center	NFP	1	1	1	1	1	0	0

Note: Control indicates Not-for-Profit (NFP), Government (Gov) or for-profit (FP) ownership. The columns indicate whether the hospital offers services or specializes in magnetic resonance imaging (mri), cardiac care (cardio), diseases of nervous system (nerv), respiratory (resp) , labor and delivery (labor), psychiatric care (psych) and organ transplant services (transplant).

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